Integrating piecewise linear representation and ensemble neural network for stock price prediction

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Abstract

Stock Prices are considered to be very dynamic and susceptible to quick changes because of the underlying nature of the financial domain, and in part because of the interchange between known parameters and unknown factors. Of late, several researchers have used Piecewise Linear Representation (PLR) to predict the stock market pricing. However, some improvements are needed to avoid the appropriate threshold of the trading decision, choosing the input index as well as improving the overall performance. In this paper, several techniques of data mining are discussed and applied for predicting price movement. For example, a new technique named Local Saturation Method (LSM) has been used to find the PLR; the weighted moving average has been applied to find recent price moves; the Shannon entropy has been used for measuring the data set complexity or nature; an intelligent system is used to select the new and important technical indexes; and finally, Ensemble Neural Networks (ENN) have been used in order to improve the overall performance. Our method has been tested by thirty problems, including up trade, down trade and steady state features. By applying all those techniques, the proposed algorithm shows good predictions with a hit rate of about 60 percent.

Key Words: Stock data, Ensemble neural network, Decision Tree, PLR method, Shannon Entropy

1. Introduction

Stock price movement is an essential issue for traders and shareholders. By being able to generate a proper prediction those concerned can engage in effective decision-making, planning, organizing, controlling the opening price, scheduling, policy making and so on. A number of factors influence the stock price such as exchange rate, interest rate, political issue, natural disaster, government policy, and the international stock market and so on. Therefore, the stock market's atmosphere is very difficult, dynamic and nonlinear, and depends on the customer's mentality. Predicting stock data with traditional time series analysis has proven to be difficult [1, 2].

The need for tools to monitor as well as control risk levels has become obvious for both industrial companies and financial institutions. The question of predictability in the stock markets is, therefore, important even outside the trading rooms. A lot of research had been done to predict the stock market movement. Stock market prediction is always an interesting field for traders and shareholders, and it is difficult to know when one should be selling the shares, buying the shares and holding shares. Very little survey or research had been done about share decision rules.

Linkai Luo, Xi Chen in [3] has integrated PLR and weighted support vector machine to forecast the stock trading signals recently. Support vector machine (SVM) performance depends on many key parameters; it is a difficult task to decide correctly. In order to get satisfactory results, one needs to engage in several experiments by altering the setting. However, they used a fixed number of threshold values, which is not good for any time series. A fixed threshold value may be fit for specific time series, but it is not suited for any time series. Also, their experimental results revealed poor accuracy. Ours is a method that can be applied for any time series analysis.

Chang et al. [4] proposed intelligent PLR with Back Propagation Neural Network (BPN) to predict stock trading decision of whether to sell, buy or hold. They used the fixed threshold value to find the turning point for PLR. Genetic algorithm (GA) was then applied to tune the threshold value. Stepwise regression analysis was used to identify the influencing factors for any trade. While their method is appropriate for finding the trading market, our proposal suggests some improvements to theirs. Furthermore, the use of GA is time-consuming. Firstly, we do not use the GA to tune the threshold value and we propose an ensemble neural network in order to improve performance. There is a possibility that the use of GA may divide the transactions of buy and sell in some parts because GA does not follow the entire sequence. To avoid this problem, Chang et al. used dynamic threshold values [5]. The basic difference in between Chang [4] and [5] is the threshold optimizing techniques.

The daily Istanbul Stock Exchange National 100 data set was predicted using the direction of movement [6]. Two classification tools, artificial neural network (ANN) and SVM was used, and ten technical indicators of both the networks were selected. Their contributions to research in stock market prediction exhibits and verifies the predictability of the stock price index direction. The simple 10 days MA and the weighted 10 days MA are used as technical indexes. They also showed better performance of ANN over SVM. The average performance of the neural network (NN) model was reported to be 75.74, and the average performance of SVM model was reported to be 71.52. Chin-Fong T. et al. [7] used majority voting and bagging for stock price prediction. They concluded that ensemble classifiers had shown better performance than single classifiers. They claimed that there was no difference between the homogeneous and heterogeneous classifier ensembles in terms of majority voting and bagging.

Abdulsalam S. O. et al. [8] used a data mining (DM) tool called a moving average (MA) method to uncover patterns and relationships, and to predict the future values of the time series data. The moving average method is a device that reduces fluctuations and obtains trend values with a fair degree of accuracy. They employed their method to describe the trends of stock market prices and predict the future stock market prices of three banks sampled.

With the development of neural networks, researchers and investors are hoping that the market mysteries can be unraveled. Although it is not an easy job due to its nonlinearity and uncertainty, many trials using various methods have been proposed. We used a new piecewise linear representation (PLR) technique called local saturation method (LSM) to find the accurate time to sell, buy and hold. The weighted moving average (WMA) carries more importance in current price movement. So, the WMA reacts more quickly to price changes than the native moving average. Data set complexity is measured by entropy value. The decision tree algorithm is used to select important influencing factors considering the customer profit. We integrate PLR and Ensemble Neural Network (ENN) to predict the stock market (PLR-ENN). Our model provides the solution for almost all kinds of forecasting problems.

The rest of this paper is organized such that Section 2 presents a review of the literature, including some related survey papers. The entire methodology is given in Section 3. This section's subsection is outlined in the following pattern: Data preprocessing, PLR, Input selection, and Ensemble neural networks. Section 4 presents the numerical results, graphical paradigm, and a comprehensive description of the findings. In this section, the thirty stock data are presented, which covers the three biggest stock markets, namely, NASDAQ Stock Market, Tokyo Stock Market, and Shanghai Stock Market. The details are provided in Section 5. Finally, conclusions and future directions of the research are provided.

2. Literature Review

Stock price forecasting has been in operation since the 1980s. The objective of long-term analysis is to gain profit from the financial market. Until now, stock pricing or financial time series forecasting is still considered one of the most complicated applications of modern time series forecasting.

J.G. De Gooijer, R.J. Hyndman [9] reviewed research into time series forecasting from 1982 to 2005. It was published in the silver jubilee volume of the international journal of the forecasting, on the 25th founding date of the International Institute of Forecasters (IIF). This review covered over 940 papers. The paper examined exponential smoothing, ARIMA, seasonality, state space and structural models, nonlinear models, long memory models, ARCH-GARCH method. They compiled the reported advantages and disadvantages of each methodology and pointed out the potential future research fields.

G. Preethi, B. Santhi [10] surveyed the recent literature in the area of NN, Data Mining, Hidden Markov Model and Neuro-Fuzzy system used to predict the stock market fluctuation. They summarized 20 research activities, published between 2009 and 2011, and listed in Table 1. They claimed that the leading machine learning techniques in stock market index prediction area is NN and Neuro-Fuzzy systems. They expected that the NN and Markov model will be used exclusively in the time series and forecasting of stock price.

Table1: G. Preethi, et all surveyed twenty papers which overlooks Neural Network, Data Mining, Markov Model and Neuro-Fuzzy system. NN, NF, DM, MA, ACO, MM, GA, T-2 indicate, respectively, Neural network, Neuro-Fuzzy, Data mining, Ant colony optimization, Markov Model, Genetic algorithm, Type-2.

Authors	Title	Publisher (year)	Area
Dase R.K. and Pawar D.D.	Application of Artificial Neural Network for stock market predictions: A review of literature	IJMI (2011)	NN
Halbert White	Economic prediction using neural networks: the case of IBM daily stock returns	Neural Networks (1988)	NN
JingTao YAO and Chew Lim TAN	Guidelines for Financial Prediction with Artificial neural networks	ICONIP (2011)	NN
T. Hui-Kuang, K.H. Huarng	A Neural network-based fuzzy time series model to improve forecasting	Elsevier (2010)	NF
Akinwale Adio T, Arogundade O.T and Adekoya Adebayo F	Translated Nigeria stock market price using artificial neural network for effective prediction	JATIT (2009)	NN
David Enke and Suraphan Thawornwong	The use of data mining and neural networks for forecasting stock market returns	Expert Systems with App., (2005)	DM, NN
K.S. Kannan, P.S. Sekar, et al.	Financial stock market forecast using data mining Techniques	IMECS (2010)	DM
Abdulsalam S. O. et al.	Stock Trend Prediction using Regression Analysis – A Data Mining Approach	AJSS journal (2011)	DM, MA
M. Suresh babu, N. Geethanjali and B. Sathyanarayana	Forecasting of Indian Stock Market Index Using Data Mining & Artificial Neural Network	IJAEA (2011)	DM, ACO
Y.L.Hsieh, Don-Lin Yang and Jungpin Wu	Using Data Mining to study Upstream and Downstream causal relationship in stock Market	*JCIS, Atlantis Press*, (*2006*)	*DM*
Md. Rafiul Hassan and Baikunth Nath	Stock Market forecasting using Hidden Markov Model: A New Approach	ISDA (2005)	MM
Ching-Hsue cheng, Tai ai-Liang Chen, LiangYing Wei	A hybrid model based on rough set theory and genetic algorithms for stock price forecasting	Information Science, (2010)	DM, GA
Kuang Yu Huang, Chuen-Jiuan Jane	A hybrid model stock market forecasting and portfolio selection based on ARX, grey system and RS theories	Expert Systems with App, (2009)	DM KM
Md. Rafiul H., B. Nath and Michael Kirley	A fusion model of HMM, ANN and GA for stock market forecasting	Expert Systems with App, (2007)	MM, NN, GA
Yi-Fan Wang, Shihmin Cheng and Mei-Hua Hsu	Incorporating the Markov chain concepts into fuzzy stochastic prediction of stock indexes	Applied Soft Computing, (2010)	MM, Fuzzy
H.L. Wong, Yi-Hsien Tu, Chi-Chen Wang,	Application of fuzzy time series models for forecasting the amount of Taiwan export	Expert Systems with App., (2010)	DM Fuzzy
S.Agrawal, M. Jindal,d G.N. Pillai	Preduction using Adaptive Neuro-Fuzzy Inference System (ANFIS)	IMECS,(2010)	NM
George S. Atsalakis and Kimon P.Valavanis	Forecasting stock market short-term trends using a neuro-fuzzy based methodology	Expert Systems with App., (2009)	NM
G. S. Atsalakis, E.M. Dimitrakakis, C. D. Zopounidis	Elliot Wave Theory and neurofuzzy systems, in stock market predictions: The WASP system	Expert Systems with App., (2011)	NM
M.H. Fazel Zarandi, et. all	A type-2 fuzzy rule-based experts system model for stock price analysis	Expert Systems with App., (2009)	T-2,Fuz.

Yuehui C. et al. [11] investigated the seemingly chaotic behavior of stock markets using the flexible neural tree ensemble technique. They examined the 7-year Nasdaq-100 main index values and 4-year NIFTY index values. Evolutionary algorithm and particle swarm optimization algorithm were used to optimize the structure and parameter of a flexible neural tree. They claimed that the most prominent parameters that affect share prices were their immediate opening and closing values. Chang et al. [12] also applied their methods in the ensemble neural network. They used AdaBoost algorithm ensembles and two different kinds of neural net, traditional BPN neural networks and evolving neural networks. Between [12] and [4], the basic difference is the use of ensemble NN instead of NN. Iffat A. Gheyas et al.[13] proposed a homogeneous NN ensemble to forecast the time series. They optimized their method through the generalized regression NN ensemble. Their method was suitable both for short-term and long-term time series.

3. Methodology

The main purpose of this research is to develop a framework that will enable one to benefit from share market. In order to meet this requirement, a simple and effective method is proposed. Also, the method is user-friendly and easy to implement. Our method has some steps, which includes data preprocessing, PLR, input selection, and ensemble neural network. Stock price prediction has always been a subject of interest for most investors and financial analysts, but clearly, finding the best time to buy or sell has remained a very difficult task for investors because there are numerous other factors that may influence the stock price [14, 15].

The entire flowchart is shown in Figure 1. Stock price depends on many factors. For this reason, the stock price always fluctuates positively or negatively. The prices also vary during the length of a day. Firstly, the raw data is taken from any stock market, and applied to the pre-processing steps. Once this is done, the turning point is found. We select some important technical indexes or some combination of technical indexes using a decision tree algorithm. The ensemble neural network is used to predict the stock market. If the output of ensemble neural network does not earn the targetted profit, the decision tree algorithm selects other indexes. The decision tree algorithm is used as an intelligent formula. Finally, the processes are stopped.

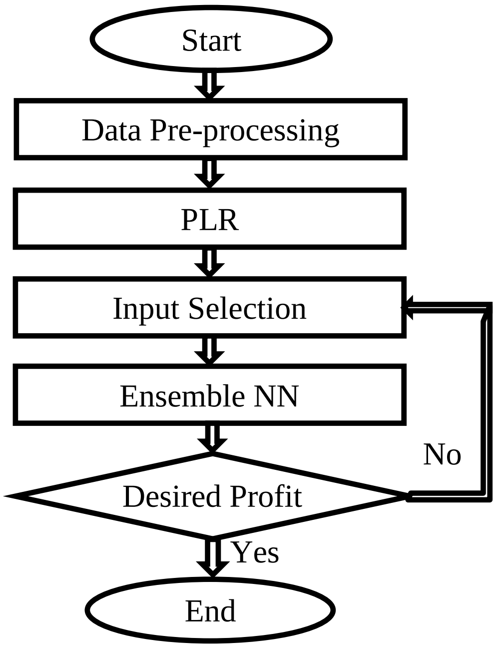


Fig. 1. Flowchart of entire proposal

3.1 Data Preprocessing

Data preprocessing has been divided into four sub-steps, including data collection, data rescaling, complexity measure, and data division, which is clearly shown in Figure 2. Each sub-step is discussed in brief in the following section.

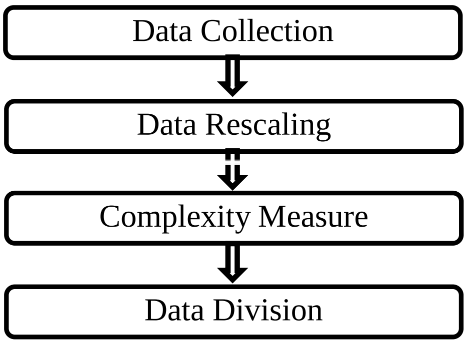


Fig. 2: Data preprocessing steps

3.1.1 Data Collection

The data was collected mainly from three big share markets, namely the Shanghai stock market (SSM), the Tokyo stock market (TSM), and the NASDAQ100 stock market. Seven data sets were collected from the Shanghai stock market. The Shanghai stock data covered a time period from 04/01/2010 to 18/08/2011, and contains approximately 391 days of transaction data. This data includes up trade, down trade and steady state. From the ten shares, four are divided into the downturn (Code: 600488, 600054, 600019, 600058), three into steady trend (Code: 600881, 600228, 600697), and the remaining three are classified as uptrend (Code: 600051, 600163, 600167) [3]. Ten data sets were collected from the Tokyo stock market. The Tokyo stock data covered a time period from 10/05/2011 to 15/03/2013, and approximately 450 days of transaction data. These data hark from five sectors, namely automotive, communication, electrical machinery, chemicals, and machinery. The selecting stock indexes are TYO: 7203, TYO: 7267, TYO: 9984, TYO: 9437, TYO: 7751, TYO: 6502, TYO: 3407, TYO: 4188, TYO: 6305; TYO: 7011, TYO: 6302. We gathered ten stock data sets arbitrary from NASDAQ100. The data covered a time period from 01/06/2011 to 15/03/2013, covering about 450 days of transaction data. The stock index selecting from the NASDAQ stock market are AAPL, AMZN, CSCO, COST, ESRX, FB, GILD, GOOG, NXPI, MSFT, and STX.

3.1.2 Data Rescaling

Stock data have nonlinear characteristic. But, it has some minimum value in a certain period. We should consider either the time variant data or the frequency data. The time variant data retains the whole characteristics of data. For this reason, only the upper portion or time variant data is taken for further analysis. What should be noted is that, if we consider all the data, the nonlinear behavior effect will be very small in any network. We use the following equation to normalize all the data in the interval (0,1). X_{old}, X_{min}, & X_{max} are the original, maximum and minimum values of the raw data respectively, and X_{new} represents the normalized form of X_{old}.

$$X_{new} = \frac{X_{old} - X_{min}}{X_{max} - X_{min}}$$

3.1.3 A complexity measure for stock time series

The main purpose behind researching the complexity of the stock market is to contract the finding into a relation that expresses the proper turning point. Also, the complexity or simplicity of the time series is gauged by knowing this information. A number of studies have been conducted to find the complexity for any time series and predict their behavior such as regular, chaotic, uncertainty, size, etc. The main types of complexity parameters are entropies, fractal dimensions, Lyapunov exponents [16]. Ahmad kazem et al. [17] used the false nearest neighbor method to find the minimum sufficient embedding dimension, and the time series phase was reconstructed to reveal its hitherto unseen dynamics. We chose the Shannon entropy from these methods to find stock price complexity. Teixeira A. et al. [18] showed that Shannon entropy effectively measured the expected value. The Shannon entropy is a basic measure in information theory by calculating uncertainty. The Shannon entropy is calculated by the following formula

$$H = -\sum_{i=1}^{n} p(x_i)\log_b \mathrm{p}(x_i)$$

Where Shannon entropy is denoted by H, x_i is a discrete value from the time series of X. The finite number of data is n, and $p(x_i)$ shows the probability density function of the outcome of x_i. We can say that the complexity of a system is due to the amount of information. Bigger entropy shows higher complexity for any time series while smaller entropy shows lower complexity to any time series. It also depends on the size. For this reason, the average entropy for hundred data is calculated from all data set. According to the entropy value, the data set is classified as high and low complexity, and this information is used in the next section. There is a strong relation between entropy and information for any data set. The Shannon entropy is good for any time series analysis. The average Shannon's entropy of 100 data is shown in table 2, where five data sets are chosen arbitrary.

Table 2: Average entropy of each 100 data in the data set

Data set	Shannon's Entropy
Toyota	6.0824
Mazda	5.0714
Softbank	6.3117
Apple	6.6239
Yahoo	6.2182

3.2 PLR

In our proposed PLR measurement, the calculation has been slightly modified from previous researches. It is very close to the local minimum and local maximum finding method or local saturation method (LSM). PLR reduces the high frequency and provides a certain decision for a certain period. Akisato Kimura et al. [19] used PLR to reduce the feature dimension from long audio signal. PLR is used to find the turning point whether it is the buy, sell or hold point. Our method also represents buy and sell, respectively, the local minimum and the local maximum. Many researchers have tended to use many methods, namely Top-Down, Down-Top and Sliding Window are popular [3].

Let us consider a time series,$y = \{y_0, y_1, y_2, \dots \dots, y_n\}$, From this time series, we will find the approximate piecewise straight lines through the following

$$y_{plr} = \{L_1(y_0, y_1, \dots, y_{nL1}), L_2(y_{0L2}, y_{1L2}, \dots, y_{nL2}), \dots \\ , L_m(y_{0Lm}, y_{1Lm}, \dots, y_{nLm})\}$$

Where $L_1, L_2, \dots, L_m$ represents the line and m represents the number of lines, and

$$L_1 = t_1 * x_1 + c_{\ 1}, \qquad L_2 = t_2 * x_2 + c_{\ 1}, \ \ L_m = t_m * x_m + c_{\ 1}$$

Here, the slope or gradient t and the line c intercept (where the line crosses the Y axis)

3.2.1 Finding Turning Point by Local Saturation Methods (LSD)

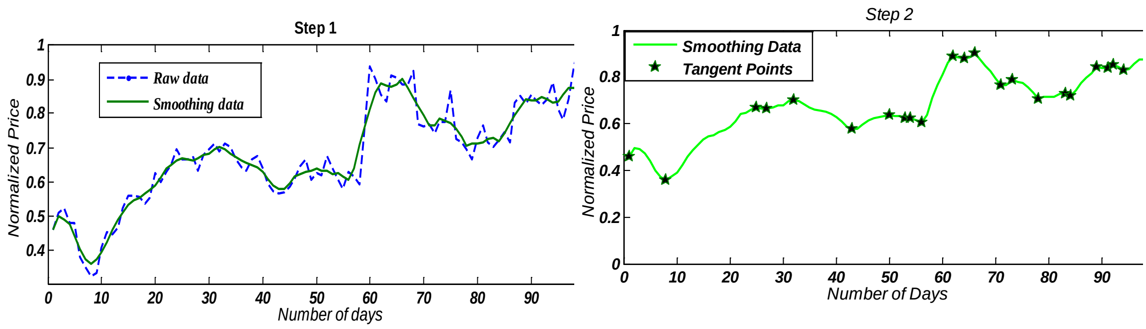
Local Saturation Method is used to find the proper buying, selling and holding time. LSM is explained using the following steps. A complete flow chart for LSD is shown in figure 3.

Step1: We have taken the closing stock price in order to find the PLR. The Weighted Moving Average method is used to smooth the data. The WMA places more importance on recent stock price moves and less weight on past data. The WMA is calculated by multiplying each of the previous day's data by a weight. This is why the WMA responds rapidly to the stock price movement [20]. The WMA works well to find the proper turning point. It helps to find big price variation points. The data sets are smoothed by reducing noise.

Step2: We perceive the tangent over the time series. These tangent points act as temporary turning points. The number of tangent points depends on how much data was taken during the data smoothing process. If we implement more data smoothing, it will lessen the number of tangent points or turning points, and vice-versa. We are taking less than ten data smoothing (such as 3 data points, 5 data points, and 7 data points smoothing).

Step 3: In this step, we identify the immature turning point. If two consecutive data points show two turning points, we consider these points as immature turning points. Then, the total immature turning points over the series are reduced. Now, we get mature turning points and straight lines are drawn from these mature turning points.

The first point and the last point are considered the default turning points. The tangent points and turning point are calculated from smoothing data, but PLR is drawn from the raw data. We calculate the slope of each straight line because of the classification class (either buy or sell or hold). Ethical examples are shown in the fig. 4 where 5 data points' smoothing are taken.



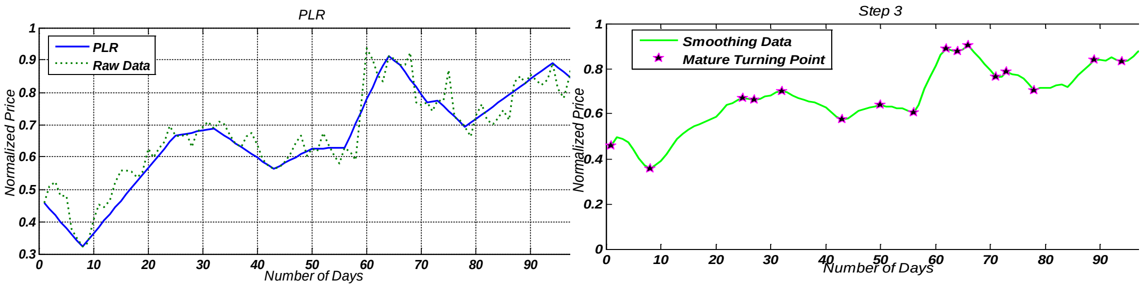


Fig. 3: Graphical representation of LSM steps

The method faces a problem when it comes to finding the appropriate moving average number. The information or the complexities of time series are used to find the accurate turning point or proper trade. We know that the complexity depends on the information of any time series. So, we wanted to establish a relationship between the MA value and the complexity value. According to the data information, we can deduce two statements:

1. If the data set has high entropy, we will take a high MA number
2. If the data set has low entropy, we will take a low MA number

The main purpose behind measuring the entropy value is to predict the MA number. Firstly, PLR has been employed to take the MA value through a few fixed numbers. Now, there is some evidence that the MA value has been taken.

Fig. 4: Complete flow chart for LSM

Our technique is one of the easiest ways to find an accurate PLR. The method we propose has a few advantages over previous ones. Firstly, there is no need to take threshold values. Threshold values maintain the full trade such as sell, buy or hold condition. This value is very sensitive to any kind of time series. We can avoid threshold selection in our method. Secondly, the optimization of the threshold values is time-consuming when effective learning is considered. If we avoid this, our learning procedure will be very easy and the learning time will be reduced. Thirdly, the Shannon entropy is used to find the complexity of the time series method, considering that the complexity of the moving average number can be automatic. Fourthly, the WMA is used to implement PLR, which helps to identify proper turning points. Fifthly, it is very easy to understand, implement and compare with the other methods. A complete flow chart for PLR is shown in Figure 4.

3.3 Input selection

3.3.1 Technical indexes

Selecting input is another key factor of time series forecasting. A number of factors influence the stock market. Also, the stock markets have some data regarding their daily stock price. It is a challenging job to find the accurate technical index combination for forecasting. The stock market is affected by a number of factors. Many researchers have investigated the many technical indicators that help to predict the trading signal [21,22,23]. There are some common factors, such as moving average, transaction volume, bias, related strength. Still, it is unknown which combination is fit for the stock market predictions.

We propose four new technical indexes which are closely related to the closing transaction price, and are an effective means to predict the stock price. Firstly, the slope of the time series can be proposed as a technical index. This technical index is very effective and essential. A positive slope reflects a positive value, and a negative slope reflects a negative value. Positive and negative values are very close to buying and selling transaction. The second proposal is a ten-day MA value of the volume of transaction. The third proposal is a ten-day MA of the amplitude of the price movement. The second and third proposed indexes are very close to the closing price transaction. Fig. 5 charts their transaction. The last proposal is the difference between the normal moving average value and the weighted moving average value. The difference in value reveals a very significant effect to finding the turning point. If the difference is high, this effect should be a turning point, and if the difference is small, this effects no action. Also, if the difference is positive, the turning point should buy point and the difference is negative, the turning point should sell point.

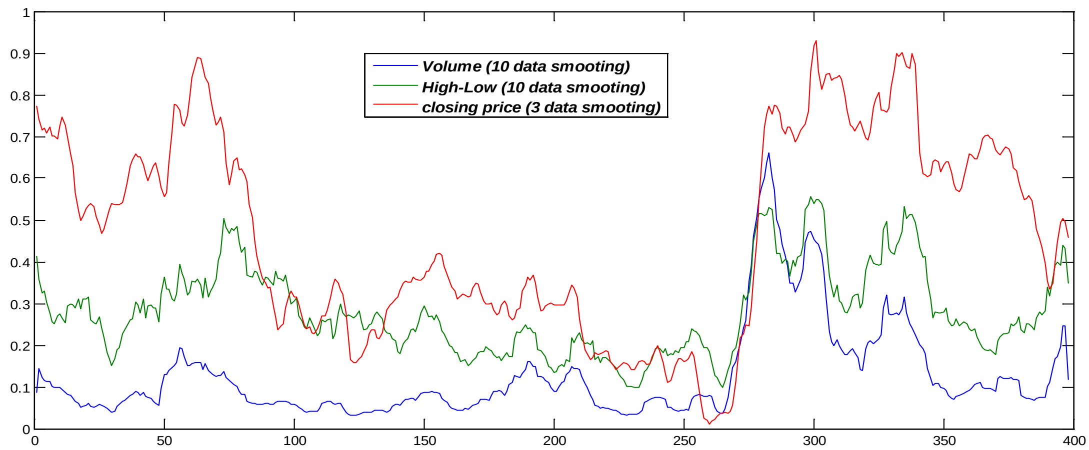


Fig. 5: Comparison graph for three technical indexes for arbitrary selected stock

3.3.2 Decision Tree

Decision Trees are common algorithms, which are used in various disciplines such as statistics, machine learning, pattern recognition, and data mining [24]. Decision trees are classifiers on a target attribute in the form of a tree structure. The observations to classify are composed of attributes and their target value. The nodes of the tree can be decision nodes and leaf nodes. Decision nodes test a single attribute-value to determine which branch of the sub-tree applies. Leaf nodes indicate the value of the target attribute [25]. There are many algorithms for decision tree induction: Hunt Algorithm, CART, ID3, C4.5, SLIQ, and SPRINT to maintain the most common. The recursive Hunt algorithm, which is one of the easiest to understand, relies on the test condition applied to a given attribute that discriminates the observations by their target values.

In most cases, decision tree implementations use pruning. This is a method where a node is not further split if its impurity measure or the number of observations in the node is below a certain threshold. The decision tree is a common situation, according to the knowledge–based recommenders. The existing knowledge domain can be incorporated in the models. The main advantages of building a classifier using a decision tree are that it is inexpensive to construct, and it is extremely fast at classifying unknown instances. Another appreciated aspect of the decision tree is that they can be used to produce a set of rules that are easy to interpret while maintaining accuracy when compared to other basic classification techniques. The decision trees are used as an intelligent technical indexes selector. The specific trees are selected for the specific data sets. The decision tree depends on the value of the profit values. Chang, et al. [4, 26] has shown a number of technical indices affecting the stock price movement. We use some input indexes, and in Table 3 presents some input indexes.

Table 3: Technical indices used in the input variables. $P_o(t),\ P_c(t),\ P_h(t), P_l(t), V(t), m, DS_N, DS_W$ respectively indicate the opening price, the closing price, the highest price, the lowest price, volume of transaction on the t^{th} day, the slope for the closing price, normal data smoothing, and weighted data smoothing.

Technical index	Explanation
The opening Price	$P_o(t)$
The closing price	$P_c(t)$
The volume of transaction	$V(t)$
The Price change in a day	$P_h(t) - P_l(t)$
The MA of transaction volume	$\overline{V}(t)$ (10MA of $V(t)$)
The MA of price changes	$\overline{P_h(t) - P_l(t)}$ (10 MA of $P_h(t) - P_l(t)$)
Slop of the closing price	m
Normal Data Smoothing	NSM
Weighted Data Smoothing	WSM
Difference of smoothing	NSM-WSM

3.4 Ensemble Neural Network:

In this section, bagging is used to produce data and NN ensemble is used to find the performance.

3.4.1 Bagging

Bagging, a shortened version of Bootstrap Aggregating, is a method that will improve the unstable prediction or classification task. Leo Breiman [27] introduced the concept of bagging to construct ensembles. The bootstrap is based on the statistical procedure of sampling with replacement. New data is created to train each classifier by bootstrapping from the original data. In the new data, many of the unique patterns may be repeated and many may be left out. Normally, the data size remains the same. Hence, diversity is obtained with the re-sampling procedure by the usage of different data subsets. Finally, when an unknown instance is presented to each individual classifier, a majority or weighted vote is used to infer the class, and when it is presented to predict, averaging is used to predict values. Table II shows the Bagging Algorithm steps.

Table 4: Bagging Algorithm

Given training set S, bagging works in the following
Step 1. Create n bootstrap samples $\{S_0, S_1, S_2, \dots \dots, S_n\}$ of S as follows
For each S_i: Randomly drawing $\lvert S \rvert$ examples from S with replacement
Step 2. For each $i = 0,1,2, \dots, n$ $h_i = learn\ (S_i)$
Step 3. Output $H =< \{h_0, h_1, \dots, h_n\}$ majority vote or averaging

There is a chance that a particular instance will be picked each time the probability is $1/n$, and will not be picked each time probability is $1 - 1/n$. Multiply these probabilities together for a sufficient number of picking opportunities, n, and the result is a formula of

$$(1 - 1/n)^n \approx e^{-1} = 0.368$$

On average, about 36.8% of the instances are not present in the bootstrap sample. So, each bootstrap sample contains only approximately $((1 - 0.368) = 0.632)$ 63.2% of the instances. If the learning algorithm is unstable, then bagging almost always improves the performance. Breiman [28] showed that bagging is effective in “unstable” learning algorithms where small changes in the training set result in large changes in predictions. Neural networks and decision trees are examples of unstable learning algorithms. Ten data sets are generated from every unit in stock market data by Bootstrap aggregation. Bagging reduces the variance, and hence improves the accuracy.

3.3.2 Neural Network

The ensemble neural network is also known as Committee Methods, Model Combiner. The ensemble is a learning model where many neural networks are used together to solve a problem to facilitate better prediction or better classification over a single neural network. There are two major concerns in this instance: firstly, the individual data sets build techniques from the unitary patterns; secondly, the question of how output is going to be combined from every data set. Many methods are available to build individual data sets. Bagging and boosting are the most popular methods. Bagging generates a diverse ensemble of classifiers by introducing randomness into the learning algorithm's input [29].

By applying bagging, we created ten individual sets from every stock data. The complete ensemble process that was used in our stock market forecasting purpose is shown in Fig. 6. PLR is created by using a number of straight lines, where each line is represented by an individual slope. Getting class, we consider a very small threshold value (nearly zero). Three classes are distinguished by the following ways

If slope value is greater than threshold class 1 [$m > T$ Class 1]

If slope value is in between as threshold class 2 [$-T \leq m \geq T$ Class 2]

Otherwise class 3 [$m > -T$ Class 3]

[Here, m and T consider as the slope value and the threshold value respectively]

Therefore, majority voting is considered as output class. Also, our network is trained by supervised NN.

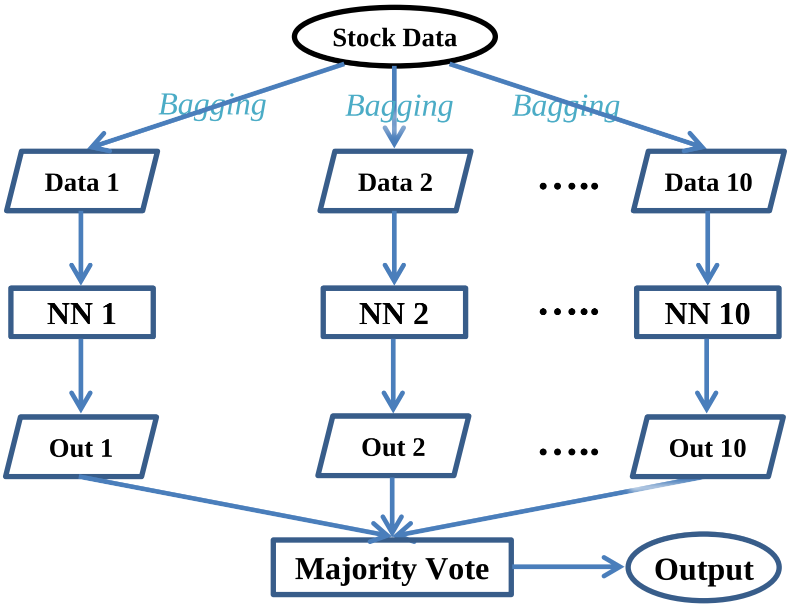


Fig. 6: Ensemble Neural Network

4. Results

The most important issue for stock market prediction is the profit or benefit for the customer or trader. To find the profit, the following formula is used

$$\text{Profit, } P = \left[\sum_{i=1}^{n} \frac{\{(1-a-c).S_i-(1+b).B_i\}}{(1+b).B_i}\right]$$

Where a, b stands for the transition cost of selling and buying of the ith transaction, c refers to the tax rate of the ith transaction. S_i , B_i represents the selling and buying price of the

ith transaction, and n signifies the number of the transition. Profit is calculated for a single share. In my methodology, a transaction is complete when the shareholder engages in the process of minimum buying and selling. Many methods do not make a profit if they do not consider the tax rate and the transition costs associated with selling and buying.

Two main factors are considered when evaluating our methods, which includes accuracy and profit. Both are considered in conjunction with customers or shareholders. To evaluate our method, seven shares are taken from the Shanghai Stock Exchange. Firstly, three shares are subjected to downtrend, two shares to the steady trend and the last two to uptrend. Table 5, 6, 7 shows the performance results of PLR-ENN. $N_B \& N_S$ represents a number of buyers and sellers, respectively.

During testing, some important considerations are made which are discussed below:

a) Two consecutive buying: It is possible, because investors can buy two times or more. But at times of sale, investors can sell all their shares at the same time.
b) Two consecutive selling: It is impossible, because investors cannot sell more without stock. The first sale is considered as a sell point, and the next one is considered as an unnecessary turning point.
c) First turning point: The first turning point should represent the buy point. If the first turning point is the sell point, it will be considered an immature turning point. Also, we are unable to sell shares without buying shares.
d) Last turning point: Last turning point should be the sell point. If instead the last turning point is the buy point, then the last point of the trade will be considered as a sell point.
e) Two turning points: If the two consecutive turning points represent two transactions days, it will be considered as an immature turning point. These two turning points should be reduced by our method. After one sell/buy decision, a minimum of two days are considered where there is no action.

The most important issue when it comes to predicting the share market is to profit from the stock market. Our method inclines towards the investor/shareholder. By considering the above condition, our method works very well. Whenever any investment is made in terms of money/any decision/any sectors, some time will be consumed in taking further decisions. Our method has found the more accurate turning points and made a significant amount of profit.

The parameter setting of the ENN, including the number of networks, transfer function, learning rate, etc. is listed in Table 5. These parameters influence the network performances.

Table 5: Parameters setting for Ensemble Neural network

Number of network	Transfer function	Learning Rate	Iteration	Momentum	Hidden Layer	Bias	Hidden neuron
10	Sigmoid	0.1	1000	1.0	01	1	3-5

The performances of the PLR-ENN are listed in Table 6,7,8 in Shanghai stock market, the Tokyo stock market, and Nasdaq stock market respectively. We evaluate our method by calculating the profit, accuracy, the number of buy points (N_B), and number of sell point (N_S).

From table 6, the Shanghai stock data covered a time period from 04/01/2010 to 18/08/2011 and the last 120 transaction data are used for the test. Among the listed stock from SSM, the index 600051 shows the highest profit, and that is 108.95% profit. The highest accuracy as shown in Table 6 is 85.12. There is no negative profit margin.

Table 6: Prediction results of SSM data by PLR-ENN

Indexes	600488	600054	600019	600058	600881	600228	600697	600051	600163	600167
Profit	21.36	14.94	23.34	62.43	33.79	76.31	37.70	108.95	80.89	97.54
Accu.	82.24	74.14	70.85	84.12	78.43	85.12	76.91	84.24	83.12	81.87
N_B	6	5	2	8	5	6	6	7	6	6
N_S	6	5	2	8	5	6	6	7	6	6

In Table 7, ten data results are presented, which is collected from TSM. TSM is the second largest stock exchange in the world by aggregate market capitalization of its listed companies. The collected data from TSM covering from 10/05/2011 to 15/03/2013 time period and the last 150 transaction data are tested. The highest and lowest profit margins, as shown in the table, are 113.08% and 38.31% for index 6502 and index 9437, respectively. The height and lowest accuracy are 88.23% and 68.25%. Our method shows very good outcome.

Table 7: Prediction results of TSM data by PLR-ENN

Indexes	7203	7267	3407	4188	9984	9437	7751	6502	6305	7011
Profit	79.52	85.27	64.49	101.50	56.89	38.31	82.70	113.08	83.32	85.16
Accu.	88.23	75.62	79.16	83.45	68.25	73.14	81.21	87.91	80.98	80.12
N_B	6	6	3	6	12	5	11	4	4	3
N_S	6	6	3	6	12	6	11	4	4	3

The prediction results of the NASDAQ100 stock market are shown in Table 8. The historic data cover the financial time-series data from 01/06/2011 to 15/03/2013 and almost 450 transaction data. The last 150 transaction data are taken to evaluate the performances. NASDAQ100 stocks data also show very good outcome. The percentage of profit cover 22.85 to 77.18 and the percentage of accuracy are 73.15 to 85.21.

Table 8: Prediction results of NASDAQ100 data by PLR-ENN

Indexes	AAPL	AMZN	CSCO	COST	ESRX	GILD	GOOG	MSFT	NXPI	STX
Profit	28.11	22.85	40.24	32.04	34.82	59.01	36.73	32.52	73.25	77.18
Accu.	77.12	75.13	82.12	80.12	82.12	85.21	75.74	73.64	82.45	73.15
N_B	7	7	7	8	7	4	4	12	4	6
N_S	7	7	7	8	7	4	4	12	4	6

The graphical representation for nine data set, including closing price and their predicted trading signal are shown in Figure 7. The data are chosen arbitrarily from three stock markets (each three). The experiment results show PLR–ENN can mine the hidden knowledge. We can say that PLR-ENN has a powerful tool for stock price prediction and has excellent generalization capability.

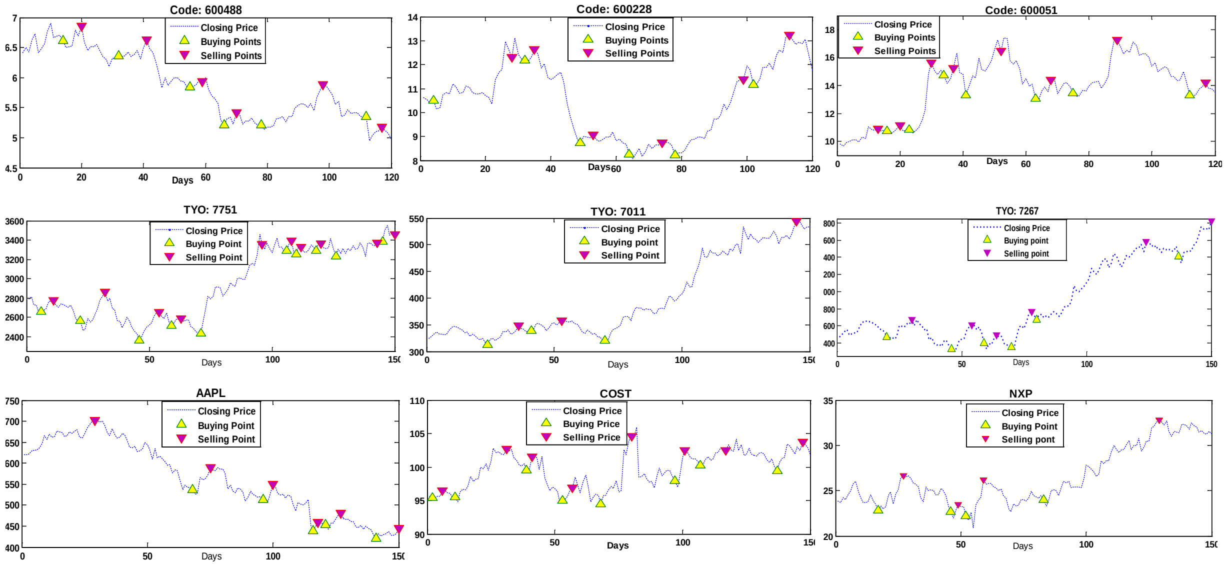


Fig. 7: Graphical example of predicting turning points.

5. Discussion

The comparison results for the Shanghai Stock Market are represented in Table 9. We can see that PLR-ENN shows the best performance. When it comes to predicting with accuracy, the PLR-ENN representation is almost double for every case. Our method does not yield any negative profit compared to the others. PLR-BPN, PLR-WSVM, and PLR-ENN shows that the minimum profit are -37.05%, -15.32%, and 14.94%, respectively, and the maximum profit are 22.61%, 50.17%, and 118.95%, respectively. Our method ensures the highest profit and the highest accuracy. So, PLR-ENN shows a higher generalized ability than PLR–WSVM and PLR–BPN.

Table 9: The comparison of values vis-à-vis PLR–WSVM, PLR–BPN and PLR-ENN. The best results are indicated in the bold font.

Indexes	Method	ACC	Profit	N_B	N_S
600488	$PLR-BNP$	33.88	-25.06	3	3
	$PLR-WSVM$	35.52	-15.32	1	1
	$PLR-ENN$	82.24	21.36	6	6
600054	$PLR-BNP$	30.21	-23.87	3	3
	$PLR-WSVM$	40.63	-2.40	3	3
	$PLR-ENN$	74.14	14.94	5	5
6000019	$PLR-BNP$	27.98	-26.46	6	6
	$PLR-WSVM$	34.72	-13.36	3	3
	$PLR-ENN$	70.85	23.34	2	2
600058	$PLR-BNP$	33.51	-37.05	3	3
	$PLR-WSVM$	44.50	22.16	1	1
	$PLR-ENN$	84.12	66.43	8	8

600881	$PLR - BNP$	33.15	1.45	7	7
	$PLR - WSVM$	33.16	4.43	2	2
	$PLR - ENN$	39.79	78.43	5	5
600228	$PLR - BNP$	31.02	4.61	8	8
	$PLR - WSVM$	39.04	33.17	2	2
	$PLR - ENN$	85.12	86.31	6	6
600697	$PLR - BNP$	31.02	4.01	7	7
	$PLR - WSVM$	39.04	33.17	5	5
	$PLR - ENN$	76.91	37.70	6	6
600051	$PLR - BNP$	33.16	22.61	2	2
	$PLR - WSVM$	36.32	50.17	3	3
	$PLR - ENN$	84.24	118.95	7	7
600163	$PLR - BNP$	27.84	11.13	6	6
	$PLR - WSVM$	35.23	9.65	2	2
	$PLR - ENN$	83.12	80.89	6	6
600167	$PLR - BNP$	37.82	-2.03	4	4
	$PLR - WSVM$	44.56	18.64	4	4
	$PLR - ENN$	81.87	105.54	6	6

Shannon's entropy numbers are used as a moving average number. But we cannot say that this technique is the most effective for every dataset. The stock data set information or entropy depends on time. It does not show the same entropy value throughout a certain period. The complexity value depends on the entropy value. It is a difficult task to find the accurate or exact number of moving averages, but the entropy measurement technique helps us to find the most accurate moving average number of predictions.

The decision tree algorithm is used as a technical index selector or more effective indexes for the specific dataset. We know that the decision tree algorithm is a knowledge-based algorithm. So, there are times when it is difficult to find effective indexes or group of indexes. It is also possible that the training period suits some indexes, but the testing period witnesses a decrease in the performance. The decision trees or decision rule algorithms are an effective method to find a group of dataset for the stock price prediction. The general advantages of decision trees are that they are well-understood, have been successfully applied in many domains, and represent a model that can be interpreted relatively easily [30].

The immature data are reduced when PLR is measured. There is little scope to delete an important turning point. In most cases, manual inspection reveals that our method can find turning points successfully. Furthermore, the weighted data smoothing, normal data smoothing, and decision rule will be applied combinely to find this solution.

Undoubtedly, the ensemble neural network has a strong predictive capability. Bagging creates data diversity, so all necessary information can train the neural network. The network will be suited to forecasting after the training. If anyone can reprocess their data properly, he or she can get a significant profit from the stock market. Also, longer time is needed to find the money that can be invested in order to get the profit. Our method does not work adequately when it comes to short term prediction.

6. Conclusion

Many researchers have investigated on how to predict the stock market trades properly as they wanted to present the benefit to the consumer or shareholder. We have charted a methodology that will foster a simple way for the consumer or shareholder considering which strategy of buy/sell/hold they can reap the advantage from. Our method shows better results than PLR-BNP and PLR-WSVM. Firstly, we employed a very simple method to measure PLR, and this method is also more useful than others. Secondly, our method improves on previous claims of accuracy. Thirdly, in most cases, our results yielded a higher margin of profit compared to other methods. Fourthly, we proposed four new technical indexes, which are very effective for finding turning point or buy/ sell/ hold point.

In the future, the proposed system can be explored by adding other factors or other soft computing techniques. Areas for further investigations are listed as follows:

1. The data smoothing number will be automatic or will approach a theoretical background. We will consider more theoretical background to find the appropriate smoothing number.
2. This paper considered the weighted moving average method of data smoothing. Furthermore, the general smoothing average, the weighted moving average, and exponential smoothing average will combine to find more proper turning point or trade point.
3. Only three stock markets are considered for this research. In the future, we will consider more well-known stock markets. Anyone can apply our method to any market and can reap a profit.
4. There are many forecasting models available. We will apply a hybrid intelligent system for prediction such as Neuro-Fuzzy, NN & Data mining, Fuzzy & Data Mining etc.

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